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Solar photovoltaic system modeling and performance prediction

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ABSTRACT

A simulation model for modeling photovoltaic (PV) system power generation and performance prediction is described in this paper. First, a comprehensive literature review of simulation models for PV devices and determination methods was conducted. The well-known five-parameter model was selected for the present study, and solved using a novel combination technique which integrated an algebraic simultaneous calculation of the parameters at standard test conditions (STC) with an analytical determination of the parameters under real operating conditions. In addition, the simulation performance of the model was compared with other models, and further validated by outdoor tests, which indicate that the proposed model fits well the entire set of experimental field test *I–V* curves of the PV module, especially at the characteristic points. After validation, this model was employed to predict the PV system power output under real conditions. The results show that the predictions agree very well with the PV plant field collected data. Thus, the operating performance of a standalone PV system located on a remote island in Hong Kong has been further evaluated with the aid of this model. It is found that the PV array power output is restricted by the status of the battery bank. This research demonstrates that the PV simulation model developed during the study is simple, but very helpful to PV system engineers in understanding the *I–V* curves and for accurately predicting PV system power production under outdoor conditions.

Contents

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1. Introduction

The energy crisis, environmental pollution and global warming are important issues for our world. In view of this, renewable energy (RE) sources, such as solar, wind, hydro and biomass energies, are being increasingly exploited to meet the energy needs and regarded as potential solutions to cope with the serious energy dilemma and environmental concerns [1,2]. This is true in both the developed and developing countries [3]. Among the renewable sources, solar energy is regarded as the most promising candidate and is expected to be the foundation of a sustainable energy economy, as sunlight is the most abundant RE resource [4,5]. The solar photovoltaic (PV) system might be superior to other RE types because it is produced silently with little O&M needs, with no direct pollution or depletion of resources, and depends solely on inexhaustible solar irradiation. Thus solar power is growing more rapidly than any other form of renewable technologies [6,7]. Solar PV holds excellent promise for large-scale electricity generation. One study [8] estimated that a PV station of area $250 \times 250\ km^2$ would be enough to meet global electricity requirements for the year 2020. As for China, its 12th Five-Year plan indicates that the cumulative installed solar PV capacity will increase from 3.3 GWp in 2011 to 20 GWp in 2015, and it is expected that this target will further soar to 47 GW in 2020 [9]. In addition, one local RE study demonstrates that PV technologies are potentially suitable for wide-scale application in Hong Kong [10], and a recent research study suggests that the government should support the large scale development of PV and stimulate the transition from fossil fuels to RE for power supply in Hong Kong [11].

Along with the rapid growth of solar PV application, better understanding of PV operating performance has become an essential topic of research. Accurate prediction of PV module power output under real weather conditions is of great importance for designers of system configurations and product selection [12–14]. Likewise, it is also crucial for engineers to evaluate PV systems operational performance. Accurate prediction of PV performance under general conditions is not possible using PV module manufacturers' specifications. Therefore, the availability of an accurate and reliable solar PV system power prediction model is of vital importance [15,16]. Over the past years, a substantial body of work has been conducted to specifically develop simulation models for PV. However, the poor accuracy and complexity of these models is not yet adequate for practical application and, requires an in-depth research study to develop an efficient and accurate PV performance simulation model. This is why this work has been carried out. The main contribution of this paper is two-fold. Firstly, a comprehensive literature review of PV mathematical models and determination methods is presented and the model involved in this study is then discussed and validated using previously collected data on file. Secondly, a case study that employed the model to predict the operating performance of a standalone PV system on a remote island in Hong Kong is described.

2. Reviews of PV device simulation models and parameter-determination methods

2.1. PV cells, modules, strings, arrays and plant

As illustrated in Fig. 1, the basic unit of a PV system is the PV cell. Dozens of PV cells are interconnected in series to form the cell series string. A group of one or more series strings is then encapsulated to produce a PV module. The modules are connected in series to increase the system voltage and form a module string. A PV array is then made up of a number of module strings connected in parallel, to increase the current of the array. The array links to a solar inverter which transforms the DC power produced by the PV array to the AC for load consumption and connection to a power grid. Generally, a PV plant is composed of a single or a number of PV arrays.

2.2. Equivalent circuit and mathematical models for PV devices (cell/module/array)

The ability to model PV device outputs is key to the analysis of PV system performance. A PV cell is traditionally represented by an equivalent circuit composed of a current source, one or two anti-parallel diodes (D), with or without an internal series resistance (R_s) and a shunt/parallel resistance (R_p). The equivalent PV cell electrical circuits based on the ideal model, a one-diode model and a two-diode model are presented in Fig. 2. These PV cell electrical power models have been widely described in the literature [17–20]. The literature also reveals that the circuit in Fig. 2c is the more commonly used [21], as it can be represented by a simple and accurate simulation model.

The outputs from these models are the current and voltage data points, which can be connected to produce the I–V curve (Fig. 3). One primary objective of the research, is to fit the predicted I–V curves to the experimental curves of the practical system, particularly at the three characteristic points: short circuit (0, Isc), MPP (Vm, Im), and open circuit (Voc, 0). The following section reviews relevant research related to PV mathematical and simulation models, and the commonly used 5-parameter model involved in this study is also discussed.

2.2.1. Ideal model

As presented in Fig. 2a, the ideal PV cell model has the simplest form since it takes no account of the effect of internal electrical series resistances and parallel resistance. Based on the Shockley theory, recombination in the space-charge zone can be neglected and the second diode term can therefore be omitted. [22]. It is acknowledged that the PV cell is neither a constant voltage source nor a constant current source. The externally measured current can be related to voltage and the relationship between them has been investigated [23,24]. Based on the Shockley and Queisser (SQ) diode equation, the ideal mathematical model for an individual PV cell is expressed as [25,26]:

$$I = I_{ph} - I_D = I_{ph} - I_0(e^{V/V_t} - 1) \quad (1)$$

where I_{ph} is the photo current (A), assumed constant along the I–V curve and proportional to the irradiance, with only a weak temperature dependency; I_0 is the diode saturation current (A); $V_t = nKT/q$ is the diode thermal voltage; n is the diode ideality factor; k is Boltzmann's constant (1.381×10^{-23} J/K); q is the absolute value of the charge on an electron (-1.602×10^{-19} C) and T is the cell temperature (K), assumed equal to the temperature of the P–N junction [27].

Nomenclature

Abbreviation

SOC	state of charge
PV	photovoltaic
RE	renewable energy
LM	Levenberg–Marquardt
ANN	artificial neural networks
MPP	maximum power point
RMSE	root mean square error
MBE	mean bias error
CLP	China Light & Power

Symbols

I_{ph}	photo current (A)
I_0	diode saturation current (A)
V_t	diode thermal voltage (V)
n	diode ideality factor
k	Boltzmann's constant (1.381×10^{-23} J/K)
q	charge on an electron (-1.602×10^{-19} C)
T	cell temperature (K)
R_s	serial resistance
R_p	parallel resistance
N_S	number of PV cells connected in series
Np	number of PV strings connected in parallel

Some studies have been carried out on the simple models involving a linear independent current source parallel to a diode [28]. However, the literature review demonstrates that the ideal cell model, in the absence of recognition of internal resistance effects, is not suitable for modeling the actual PV cell current and voltage relationship [23].

2.2.2. One-diode model taking account only of Rs (4-p model)

Fig. 2b illustrates the equivalent PV cell electrical circuit for the series resistance case. This is the so-called four-parameter (4-p) model [29–36], in which the parallel resistance is considered as infinite and thus its effect is not taken into account. Its mathematical model is presented as:

$$I = I_{ph} - I_D = I_{ph} - I_0(e^{V+IR_s/V_t} - 1) \quad (2)$$

In Ref. [37], the 4-p PV model was proposed, and incorporated into the transient simulation program TRNSYS. This model was used to estimate and optimize the performance of a pumping system PV installation [31,38]. The model, based on four parameters, was used to simulate three types of PV panels, each differently constructed, one with thin film, another with polycrystalline silicon, and the third with mono-crystalline silicon materials [39].

Recent research study, however, shows that the 4-p model which ignores the effects of shunt resistance is inadequate in fitting experimental *I–V* and P–V data in the current-source operation [13]. Additionally, the four-parameter and five-parameter PV analytical models are compared [40,41], demonstrating that the simplified four-parameter model does not satisfactorily reflect the effect of high temperature on the current, and leads to a less accurate prediction of current than the five-parameter model.

2.2.3. One-diode model considering R_s and R_p (5-p model)

To improve the accuracy of the simulation model, parallel resistance is thus introduced in the one-diode model. This is the well-known five-parameter (5-p) model, shown in Fig. 2c and represented by Eq. (3).

$$I = I_{ph} - I_D - I_p = I_{ph} - I_0(e^{V+IR_s/V_t} - 1) - \frac{V+IR_s}{R_p} \quad (3)$$

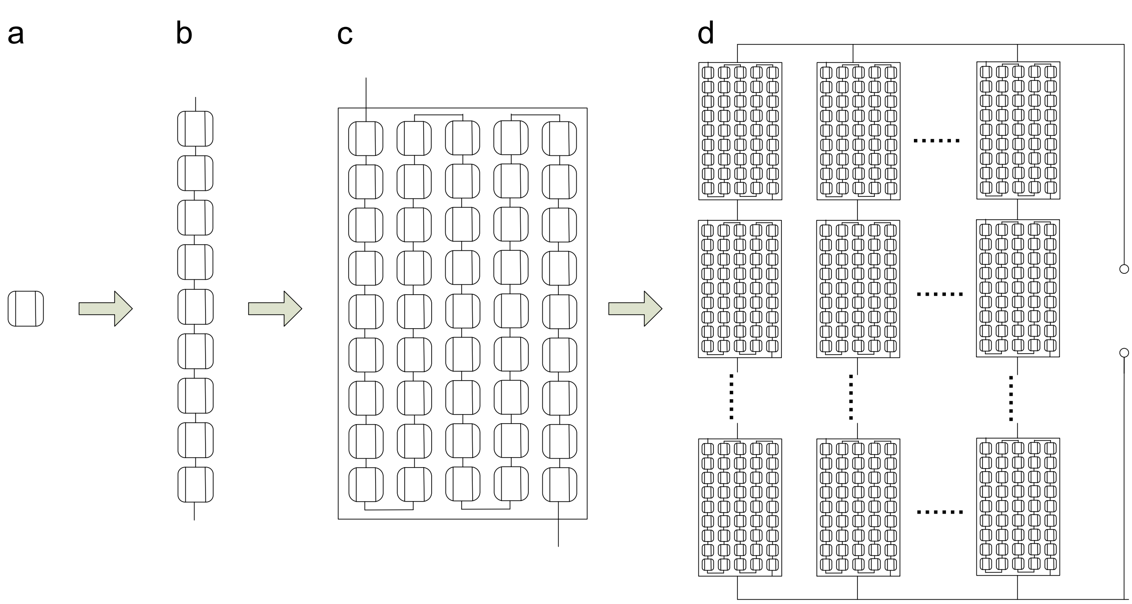

Fig. 1. Physical configuration of photovoltaic cell (a), cell series string (b), module (c) and PV array (d).

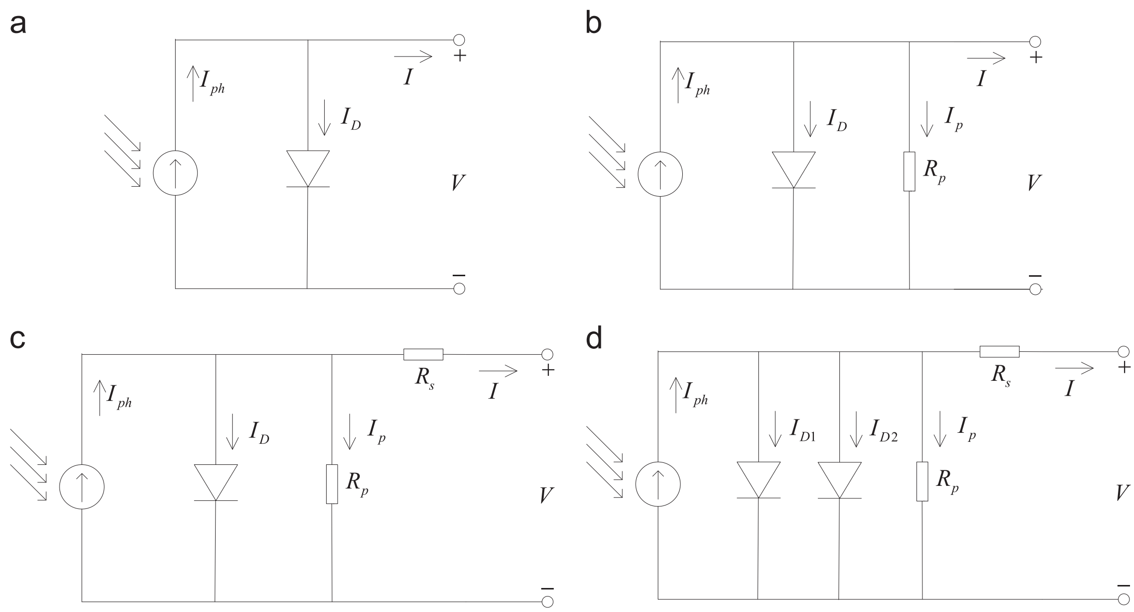

Fig. 2. Equivalent PV cell electrical circuits: (a) ideal model; (b) one-diode only with R_s (4-p model); (c) one-diode with R_s and R_p (5-p model) and (d) two-diode models (7-p model).

It is widely acknowledged that both series resistance R_s and parallel resistance R_p can affect the I–V characteristics of a PV device. In general, the parallel resistance reduces the available electrical current, and the series resistance affects the output voltage.

Recently, a new method to extract the five parameters has been developed by Ma et al. [42] and Bai et al. [43]. The dynamic behavior of a 3.2 kWp photovoltaic system was evaluated in real conditions using the 5-p model [44], and the output of a partially shaded PV module was also modeled based on the 5-p model [45]. Five of the recent and most cited articles on the 5-p model [12,16,27,46,47] were discussed [6], with respect to the mathematical models themselves, the parameter extraction procedures, and the major hypotheses and simplifications involved. The Literature review shows that much research has been carried out in developing the 5-p model, also providing some directions for improvement and/or simplification to obtain the five parameters (I_L, I_0, V_t, R_s, R_p), and results from those studies demonstrate acceptable levels of accuracy [12,40,49–55].

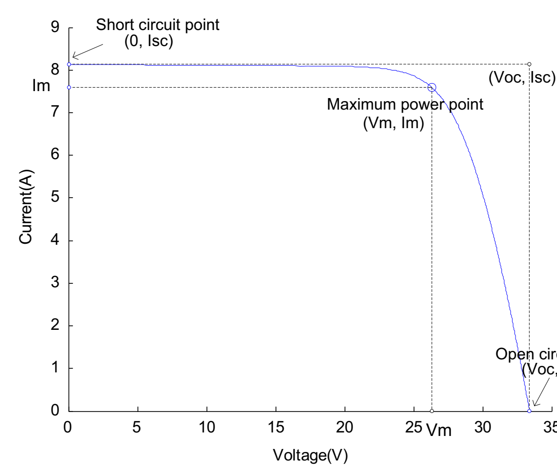

Fig. 3. PV module I–V characteristic curve with three characteristic points.

2.2.4. Two-diode model

The commonly used one-diode model can achieve acceptable accuracy, but the reality is that the saturation current of the PV cell is the result of a linear superposition of charge diffusion and recombination in the space-charge layer [56]. This means that the saturation current is contributed to by two Shockley terms, i.e. two diodes. Therefore the two-diode model, also called the double-diode model, was proposed [56–63]. The schematic diagram of the equivalent electrical circuit is illustrated in Fig. 2d and the mathematical model is expressed as:

$$I = I_{ph} - I_{D1} - I_{D2} - I_p = I_{ph} - I_{01}(e^{V+IR_s/V_{t1}} - 1) - I_{02}(e^{V+IR_s/V_{t2}} - 1) - \frac{V+IR_s}{R_p} \quad (4)$$

where I_{D1} and I_{D2} are the currents passing through the corresponding diodes. As for the single-diode model with R_p and R_s (five-parameter model), the internal series and shunt resistances affect the output voltage and current, respectively.

The two-diode model can achieve greater accuracy, particularly at low irradiance level and during partial shading conditions [64]. The inclusion of an additional diode, however, increases the number of computed parameters. Eq. (4) indicates that this model is quite complex, being a nonlinear and implicit equation with two exponential terms and up to seven unknown parameters., The computational time is, therefore, relatively long [18,20]. In addition, other new coefficients are introduced into the equations, further increasing the computing burden.

Many attempts have been made to reduce the computational complexity of the two-diode model, but they appear to be unsatisfactory [20]. Some researchers assumed the diode ideality factors to be n1 = 1 and n2 = 2 to simplify the model. The latter is an approximation of Schokley–Read–Hall recombination in the space charge layer in the photodiode [65]. Although this assumption is widely used while it does not always hold true [66]. In Ref. [20], the authors developed an improved two-diode model and simplified the current equation, resulting in a requirement for only four parameters. The reverse saturation currents I_{D1}, I_{D2}, however, are then forced to be equal in magnitude. Such simplification may result in some inaccuracy although computation time is reduced.

The two-diode model provides higher PV cell modeling accuracy, but it was not selected for this study for the following two reasons. One is that the recombination incurred by the second diode dominates at low voltage and low irradiance [46,67], conditions seldom selected for simulation studies. The other reason is that the

parameter determination would be very complicated as another diode has been added.

2.2.5. Other models

In addition to the above models, the three-diode model [68] has also been studied, but not to a great extent, because of the calculation complexity. Some research investigated thermal models to simulate PV performance, such as one based on overall heat loss coefficient [69,70] and one based on thermal capacitance [70]. These models are not suitable for wide use usually because of insufficient information from the module manufacturer. Mathematical modeling of PV module output taking account of solar cell mismatching and the interconnection ribbon was proposed in [71]. An empirical general photovoltaic devices model was studied in [28], and a method called APTIV, which fits the *I–V* curve in two different zones was used to extract the solar cell physical parameters [72]. Accuracy, however, focuses only on the three characteristic points, rather than the complete characteristic curves.

2.3. Determination methods for solving model parameters

After developing the simulation model, determining the unknown model parameters is challenging, as the simultaneous equations are usually non-linear and include exponential terms. Mathematical techniques, therefore, usually are employed to extract the unknown parameters. In general, the degree of complexity of the simulation model determines which one of the methods is the most suitable [46]. Many studies have been conducted attempting to solve the above equations. Basically, to calculate the model parameters, analytical and numerical methods are used.

2.3.1. Available analytical solutions

The traditional analytical approach introduces a series of simplifications and approximations, to obtain simpler solutions and avoid bringing obvious errors to the model [40,46]. Many publications have reported on analytical methods [31,40,47,73–77]. In addition to avoid modeling complexity, a data-based approach has been presented [39]. Sometimes errors in the unknown parameters, however, can be very significant if the key points on the *I–V* curves are not correctly specified [18].

2.3.2. Available numerical solutions

Numerical solutions, also known as algebraic solutions, employ powerful mathematical tools and iterative methods to solve the implicit non-linear equations associated with PV simulation models. Numerical solutions are widely used in systems engineering because they offer a reasonable compromise between simplicity and accuracy [78].

Various numerical techniques, such as resistive-companion methods [79], non-linear least squares optimization [80] the Newton–Raphson method [27], the bisection method [49], and the equation solver EES [12], have been proposed for the simultaneous solution of these non-linear equations. An iterative programming method was introduced in [34,81] which estimated the parameters associated with PV simulation models. This method was also improved using interpolation techniques [82]. Most of those approaches, however, demand much computing effort. Another numerical iterative method, the Levenberg–Marquardt (LM) algorithm, was employed in [40,46,56,59] to solve the implicit non-linear equations, proving to be a robust method possessing sufficiently rapid convergence characteristics. However this technique requires good initial estimation of parameter values to attain convergence, particularly in the case of the two-diode model [6]. In some cases heuristic solutions need to be sought [20]. A simulation model has also been implemented using Microsoft Excel VBA macros [16].

The performance simulation models of PV devices are also available in some existing software, such as PVWATTS, PVMOD, PVFORM, INSEL, PVWATTS, PHANTASM, TRNSYS, P-Spice, PV-DesignPro, Solar-Pro, PVcad, and PVsyst [6,15,42,64,83,84]. In addition, the PV model has been solved using the LSODI FORTRAN Livermore solver [85], the FORTRAN computer code was also programed in [86,87] and added to the standard TRNSYS library with sub-programs, to solve the *I–V* equation numerically. A PV simulation model was written in the C language and run on a PC using a Borland C^{++} compiler [53]. An intricate PSpice software-based simulation was presented in [88]. Furthermore, many studies solving PV simulation models in the Matlab/Simulink environment have been reported [41,44,52,62,64,89–92], as this tool provides a graphical interface for models constructed as block diagram. Such models can be easily connected together so as to simulate a particular specific system [93]. However, these software/tools are either quite sophisticated and intended for the advanced users[6], or too general with results that are not so accurate [42]. Usually new coefficients are introduced into the equations, thereby increasing the computational loading [64]. They are also relatively expensive and unnecessarily complex [94].

Recently, various evolutionary algorithms have been utilized for the parameter extraction of PV device simulation models, such as the genetic algorithm [95,96], differential evolution [19,97], and particle swarm optimization [98]. Some studies have been made on PV device *I–V* curves using artificial intelligence [19,20], such as fuzzy logic [99,100] and artificial neural networks (ANN) [30,41,50,78,101–103]. Despite the more accurate results, artificial intelligence techniques require extensive computation, and ANN requires a large amount of data for network training purposes.

3. The model and parameter-determination method employed in this study

The most important factor affecting the accuracy of PV system simulation is the modeling of the PV cell. Based on the above literature review of PV modeling, it can be concluded that although the two-diode model is a preferable choice in terms of accuracy, its computational requirement is much more demanding in comparison to the equation with the one exponential term only, i.e. the well-known five-parameter model. This makes the two-diode model less attractive than the latter [20]. The five-parameter model (Fig. 2c and Eq. (5)) offers a reasonable compromise between computational complexity and accuracy, and hence was selected for this study. The mathematical model in Eq. (8) is employed for modeling one single solar cell output. The PV array may be composed of several

Fig. 4. The installed PV system on a remote island in Hong Kong (19.8 kWp).

modules connected in series and several strings in parallel. The output current I_A and output voltage V_A of a PV array with N_S cells in series and N_p strings in parallel, therefore, is expressed as:

$$I = N_p I_{ph} - N_p I_0 (e^{\frac{1}{V_t}(\frac{V_A}{N_s}+\frac{I_A}{N_p}R_s)} - 1) - \frac{N_p}{R_p}(\frac{V_A}{N_s}+\frac{I_A}{N_p}R_s) \quad (5)$$

Similar mathematical PV array models can be found in [85,104]. The model proved able to be directly developed by Matlab/Simulink and other electromagnetic transient simulation programs [51]. As a result, the characteristic *I–V* or *P–V* curves and characteristic points can be obtained easily and accurately.

In this study, a novel theoretical model was developed based on the five-parameter model. The model development details and determination method can be found in the authors' publication [42]. Only a few inputs are needed and all can be directly obtained from the manufacturer's datasheet. Five simultaneous equations were developed based on the three characteristic points and thermal properties of the PV panel, according to the specification provided by the manufacturer. By implementing the equations in the Matlab environment using the Levenberg–Marquardt algorithm, the five model parameters (I_{ph}, I_o, V_t, R_s and R_p) under standard test conditions (STC) were calculated numerically. At this stage, a close guess of initial parameter values is required to attain convergence. The analytical method was then employed to extract the parameters under various operating conditions, by taking into account the effects of irradiance and cell temperature. The integrated solution technique, therefore, can determine the model parameters under any general conditions. Finally, the parameters, which involved the superposition of irradiance and temperature effects, were substituted in Eq. , to obtain the PV module/array *I–V* characteristic curve and maximum power output.

A major contribution of this work has been to develop a PV module/array simulation model and define an integrated method to extract, both simply and quickly and with a sufficient degree of precision, the electrical parameters related to the PV array of a real system. The final objective was to apply this model to predict the operational performance of PV systems in the field, such as power production given the variability of actual weather conditions. It was envisaged that such proposed work would be very relevant to the needs of PV power system designers and engineers who require simple, fast and accurate models for PV systems.

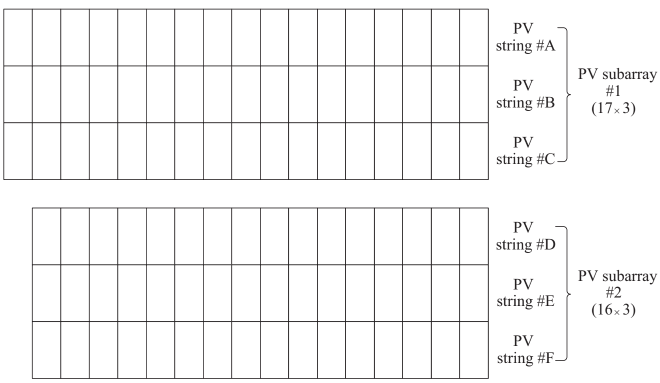

Fig. 5. PV system configuration.

Table 1
The key specifications of the Suntech STP200-18/Ub-1 PV panel.

Characteristics	Value
Open - Circuit Voltage (Voc)	33.4 V
Voltage at maximum power point (Vmp)	26.2 V
Short - Circuit Current (Isc)	8.12 A
Current at maximum power point (Imp)	7.63 A
Maximum power at STC (Pmax)	200 Wp
Number of cells connected in series	54
Temperature coefficient of Voc	$-(0.34 \pm 0.01)$%/°C
Temperature coefficient of Isc	$-(0.055 \pm 0.01)$%/°C

4. Model application

4.1. PV plant and PV module in this case study

The proposed model and determination method was implemented in a case study on a standalone PV system (Fig. 4), located on a remote island (22.3°N, 114.2°E) in Hong Kong [105–107]. At present, there are about 60 residents on this island and the number will increase to 100 in the future [108]. In 2008, a 19.8 kWp PV system was installed to supply power to the local residents. As shown in Fig. 5, there are two subarrays. PV array #1 consists of three parallel strings (#A, #B and #C) with 17 PV modules connected in series, and all modules are connected to one PV inverter. The subarray #2 is similarly configured as 16 × 3 and connected to the other inverter. This PV plant, therefore, contains 99 polycrystalline modules in total. The key specification of the module (model: STP200-18/Ub-1) provided by the manufacturer is presented in Table 1.

In this PV system, the long-term environmental data (solar irradiation and ambient temperature) and the operating performance data such as instantaneous power output, the battery bank status and electricity consumption have been continuously recorded by the data collection system at intervals of five minutes since commissioning of the system.

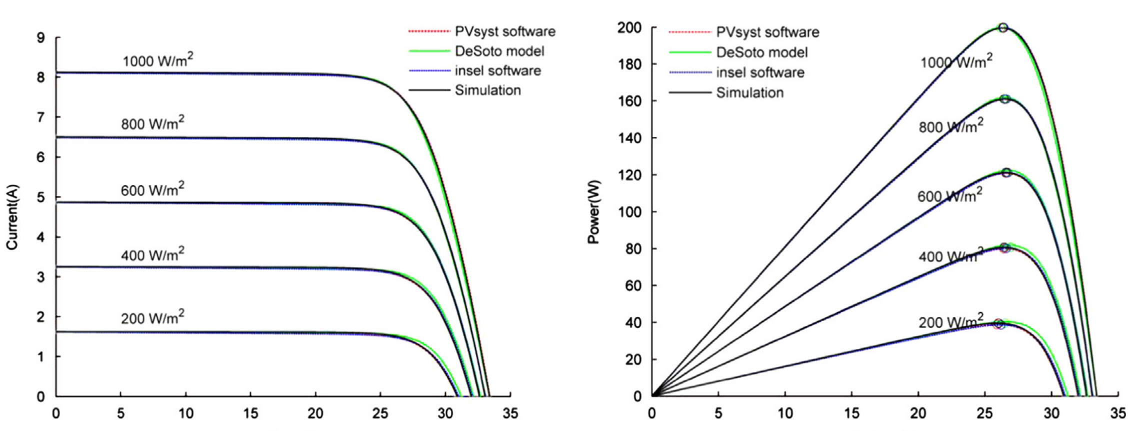

Fig. 6. PV module's *I–V* curves and *P–V* curves under different solar radiation intensity (Tc = 25 °C).

4.2. Simulation results and validation with field collected data

The simulation results from the model in Matlab were compared with those from the DeSoto model, PVsyst software and insel software under a wide range of cell temperatures and solar radiation levels. Fig. 6 presents the *I–V* curves and the *P–V* curves for solar radiation ranging from 200 W/m^2 to 1000 W/m^2 when the cell temperature is 25 °C. It can be seen that only a slight difference between the DeSoto model results and those of the other models can be found in the knee of the curves, which may result from the ideality factor being less than one. Other curves agree well. Fig. 7 illustrates the studied module's *I–V* curves and *P–V* curves under different cell temperatures (irradiance = 1000 W/m^2). Similarly, the curves from this proposed simulation model agree well with those from the PVsyst software and the insel software, and only a small difference was observed to the DeSoto mode results.

The graphic results illustrate that the simulation model results of this study agree well with those from other software models,

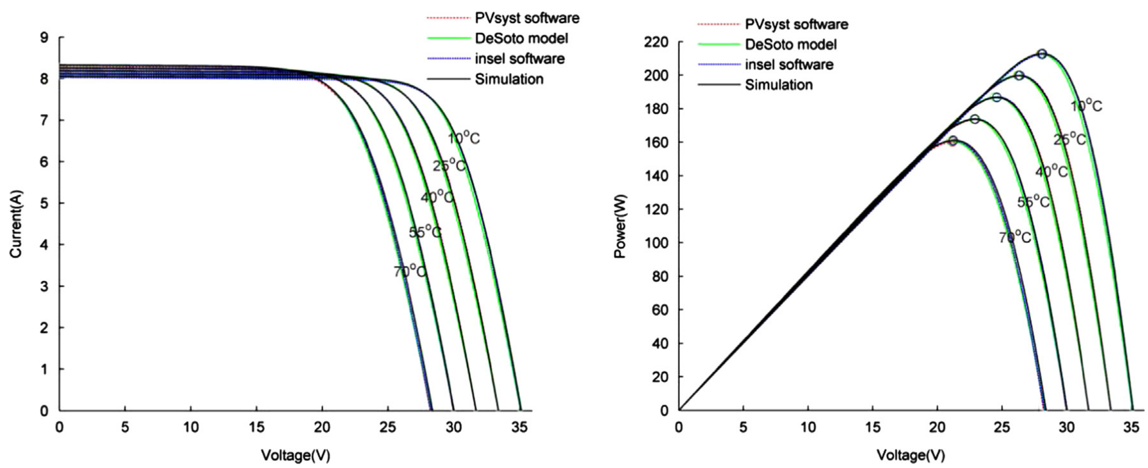

Fig. 7. PV module's *I–V* curves and *P–V* curves under different PV cell temperature (irradiance = 1000 W/m^2).

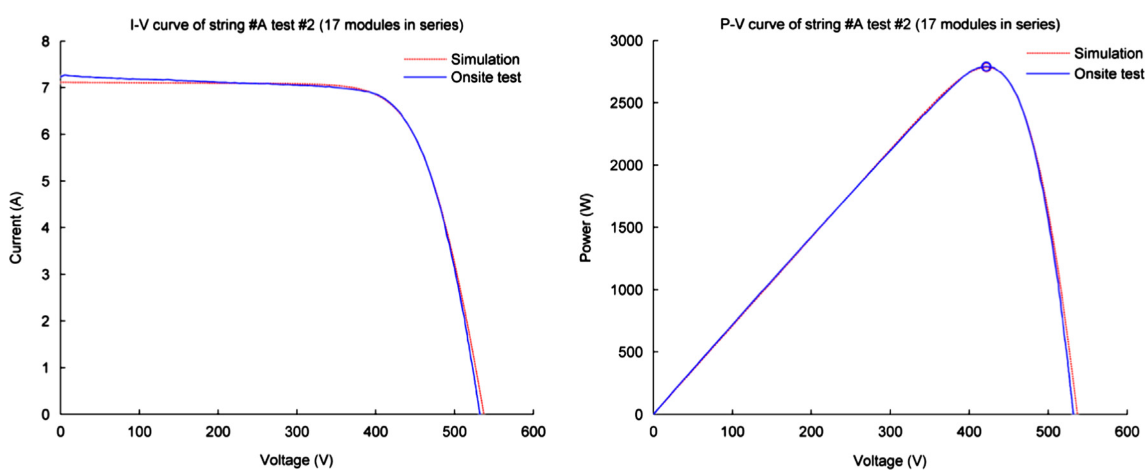

Fig. 8. Measurement and simulation results of PV module string A.

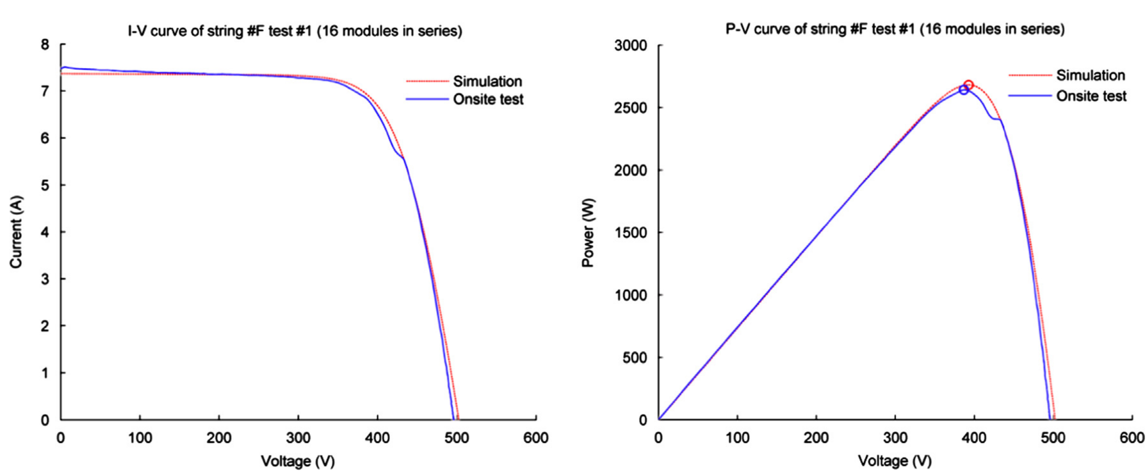

Fig. 9. Measurement and simulation results of PV module string F.

which validates the simulation model allowing it to be used for PV performance prediction in the next stage.

The accuracy of this model and determination method was further verified by comparing calculated *I–V* curves from the simulation model with field collected *I–V* curves for the six PV strings, which were measured on 29th December 2010. The data was collected by the portable *I–V* checker MP170 from EKO, which can measure specifically the onsite *I–V* curves of a PV module/string/array.

Using PV string A (PV array #1) results as an example, Fig. 8 shows that the simulated curves coincide well with the experimental results. The relative errors of the Pmpp are smaller than $\pm 1\%$. Fig. 9 illustrates the simulation and onsite measurement results for the PV string F (PV array #2). The field collected curve shows that this PV string did not function well because an obvious inflection point can be seen around the maximum power point (MPP). Similar features were observed in other measurements relating to the PV string F. The inflection points on the PV string F measured curves indicate that the string may have defects or else is shaded.

5. Photovoltaic system performance prediction

5.1. PV array power output prediction

With the simulation model developed, the *I–V* and *P–V* curves for any general set of weather conditions can be predicted accurately, and the maximum power output estimated. Real-time power generated by the two PV arrays was recorded by the existing PV system. To compare predicted and measured power of the PV arrays, three typical cases, each with different weather conditions were investigated, i.e. sunny days, semi-cloudy days and cloudy days. The cases had different amounts of average daily solar irradiation from 6:00 to 18:00. For each case, the simulation model was verified by selecting one sample day with at least 120 datasets. Detailed information for the three examples is given in Table 2.

5.1.1. A. Case I: sunny day

In the case of the sunny day of 12th October, 2010, the daily average solar irradiation was about 599 W/m^2, peaking at 963 W/m^2 at 12:00 (Table 2). The predicted and measured power outputs of the PV array #1 on that day are illustrated in Fig. 10. The predicted power–output curve followed the measured values trend reasonably well. Relationships with solar radiation are also presented. In the morning, the simulated and measured power output increases gradually coinciding with the irradiance intensity. However, obvious differences between the irradiance and power curves can be seen around the solar noon. Such difference is mainly caused by the high PV cell temperature. In the afternoon, the cell temperature decreases with solar radiation, and thereafter the effect of temperature on power reduction is not so obvious, thus the predicted power and measured power outputs are both close to the irradiance profile.

Table 2
The weather conditions of the three cases.

Data type	Date	Irradiance (W/m^2)		Ambient temperature (°C)		Module temperature (°C)	
		Max.	Ave.	Max.	Ave.	Max.	Ave.
Case 1: sunny day	12th Oct 2010	963	599	31.9	29.6	55.8	46.7
Case 2: semi-cloudy day	12th Feb 2012	930	224	21.2	14.3	37.4	27.0
Case 3: cloudy day	16th May 2011	509	148	27.7	24.6	40.6	33.7

5.1.2. B. Case II: semi-cloudy day

The second case concerned a semi-cloudy day. On that sample day, the solar radiation fluctuated greatly from 0 to 930 W/m^2, averaging at 224 W/m^2 (Fig. 11). Similarly, the modeled power–output curve was seen to match well with the measured data. Some differences were found at some peak points, which may be

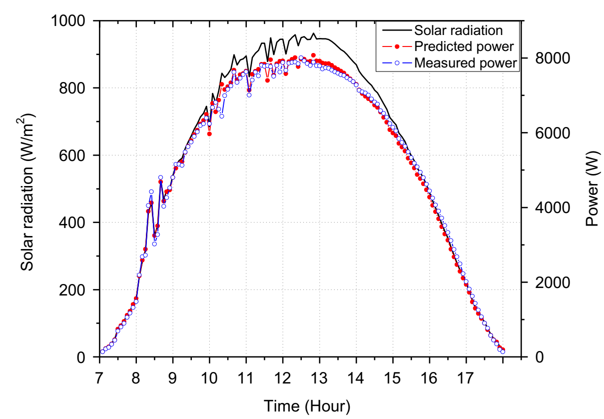

Fig. 10. Predicted and measured power-output profile of PV array #1 on 12th Oct 2010 (sunny day).

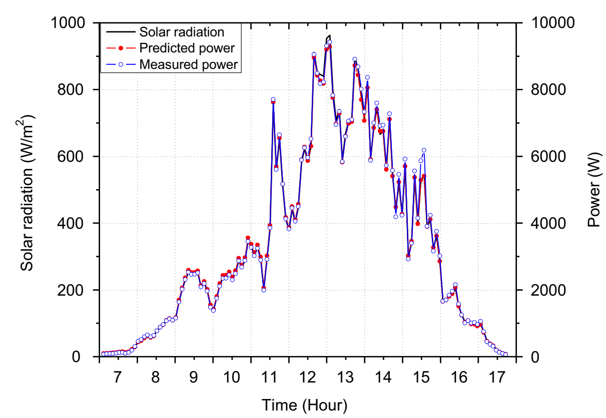

Fig. 11. Predicted and measured power-output profiles of PV array #1 on 12th Feb 2012 (semi-cloudy day).

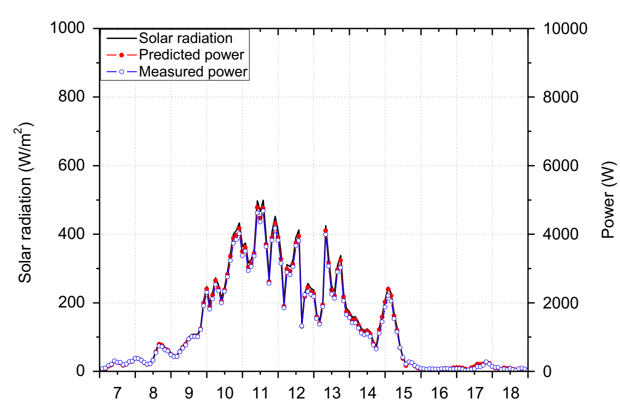

Fig. 12. Predicted and measured power-output profiles of PV array #1 on 16th May 2011 (cloudy day).

caused by solar radiation sensor measurement error because of its rapidly variation. The effect of the cell temperature on PV array performance is not significant since the average module temperature was only 27 °C, very close to the standard test condition.

5.1.3. C. Case III: cloudy day

The measured data on 16th May, 2011, was selected to validate the simulation result for an extremely cloudy day (Fig. 12). It can also be seen that the predicted and measured data show consistent agreement throughout the day, demonstrating high accuracy for this simulation model, even under low irradiance levels. On that day, the simulation model slightly overestimated the actual current values, which may represent PV panel deterioration because of aging, soiling and other factors.

5.1.4. D. Performance indicators of the simulation model

To quantify the performance/accuracy of the proposed model, the coefficient of determination R^2 was employed in this study to measure how well a simulation model follows the variation in onsite collected data. This indicator has been used in publications [3,40,101] as a statistical tool to evaluate the simulation performance of power or current predictions. The coefficient of determination is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - f_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{6}$$

where y_i is the field measured/observed data, f_i is the associated modeled/predicted data, and $\overline{y}$ is the arithmetic mean of the field data, i.e. $\overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

As presented in Table 3, the R^2 values of the arrays #1 and #2 for three weather conditions are quite high, ranging from 0.992 to 0.998. These calculated R^2 values are much higher than those seen in the literature [3]. A strong correlation, therefore, exists between the predicted and measured data, demonstrating the superior performance of the simulation model for general weather conditions.

The simulation performance was also evaluated by calculating the root mean square error (RMSE) which measures nonsystematic error, and the mean bias error (MBE) which measures systematic error. These two indicators are widely employed in the literature [75,101,109]. They are nondimensional (error/power) and expressed as a percentage (%) value. The parameters are defined as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{f_i - y_i}{y_i} \right)^2} \tag{7}$$

$$MBE = \frac{1}{n} \sum_{i=1}^{n} \frac{f_i - y_i}{y_i} \tag{8}$$

where the field measured data y_i is considered to be the ‘real value’, and the model predicted data f_i to be the ‘calculated values’.

Table 3 shows that both the RMSE and the MBE values for PV arrays #1 and #2 are very low, indicating very good agreement between predicted and measured power outputs. These performance indicators demonstrate that the proposed model is not only suitable for *I–V* characteristics modeling but also for any general purpose power prediction.

Table 3
performance statistic of the proposed model.

Data type	R^2		RMSD (%)		MBE (%)	
	Array #1	Array #2	Array #1	Array #2	Array #1	Array #2
Case 1: sunny day	0.992	0.997	0.07	0.04	−0.02	−0.002
Case 2: semi-cloudy day	0.998	0.998	0.10	0.10	0.03	0.04
Case 3: cloudy day	0.997	0.993	0.26	0.29	0.03	0.06

5.2. Energy production prediction

The measured and predicted energy production from PV arrays #1 and #2 is illustrated in Table 4. The differences errors between them are within 5% for the three weather conditions, indicating the proposed model can estimate PV system energy production accurately.

5.3. Performance evaluation of the PV system using this model

The operating performance of a PV system was simple to evaluate, with the aid of the validated simulation model. The potential power output was predicted using the model and compared with that from the measured data, and some possible reasons for the obvious differences were then examined.

For this standalone PV plant located, on a remote island, the excess power from the PV arrays after servicing the load, should be delivered to the batteries. However, the battery charging rate is usually limited by the two major factors, the state-of-charge (SOC) and the floating charging voltage (or the terminal voltage) [110]. When either the charging voltage or the SOC are greater than their upper limits, the battery bank and the control center take some self-protection actions, and PV arrays will be partially or totally shut off or disconnected from the load and the battery bank, to protect the PV arrays, battery bank and the electrical appliances on the load side.

The measured and predicted power-output profiles of the PV array #1 on 30th May 2011, used as an example to explore the reasons for PV array power reduction, are presented in Fig. 13. At the beginning of that day, the measured and calculated power outputs have a close relationship with the solar radiation fluctuation, while the measured power dropped down suddenly at almost 14:00 in the afternoon. Thereafter an obvious difference between the measured and calculated power outputs can be observed until

Table 4
Measured and predicted energy production on the three example days.

Data type	PV array #1			PV array #2		
	Measured energy (kWh/day)	Predicted energy (kWh/day)	Error (%)	Measured energy (kWh/day)	Predicted energy (kWh/day)	Error (%)
Case 1: Sunny day	61.22	59.91	−2.14	56.45	56.38	−0.11
Case 2: semi-cloudy day	36.46	36.19	−0.76	33.58	34.06	1.43
Case 3: cloudy day	15.36	15.87	3.32	14.26	14.94	4.76

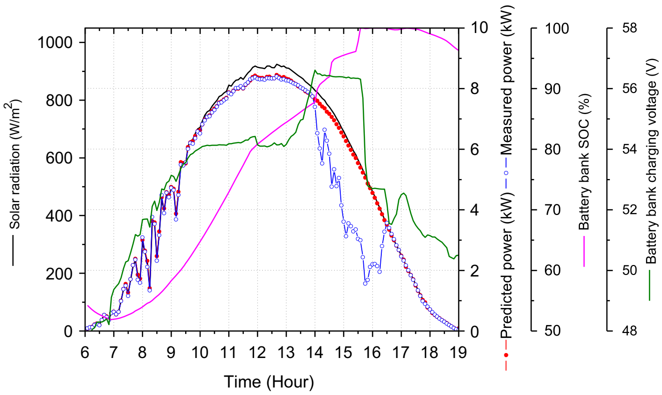

Fig. 13. Predicted and measured power-output of PV array #1 on 30th May 2011 with SOC and charging voltage profile.

about 16:30. The irradiance profile and predicted power curve, however, indicate that the PV array has the potential to generate more power. This figure reveals that the PV arrays were partially shut off and disconnected from the load and battery bank. The possible reasons for this can be gauged by using the curves of the battery bank SOC and the charging voltage. The reduction in PV array power generation between 14:00 and 15:30 was possibly due to the high battery bank charging voltage being greater than the upper limit of 56.4 V (2.35 V for each battery cell). The continuous decrease in PV power from 15:30 to 16:30 results from the fully charged battery bank, with the SOC reaching 100%.

This is just one example to show how power reduction of the PV generator can be due to a fully charged battery storage system. In fact, there are many days, mostly in the afternoons of sunny days, which have the potential to generate much more power, but the PV array output is partially or even totally cut off from the inverter. Theoretically, sufficient storage capacity can help to achieve higher PV power output ratios in the standalone system [105]. In addition, the training of local residents in the better utilization of the energy supplied by the PV array and battery bank, based on the weather and the energy stored in the battery bank (i.e. SOC), could contribute to improving the mismatch between power production and consumption.

6. Conclusions

Various mathematical models for PV systems and corresponding determination methods were reviewed in detail.. The five-parameter model was then employed in this study and solved combining analytical and numerical methods leading to rapid convergence. The validation of the model was carried out by comparing simulation results produced by other models and software, and its performance was further validated by comparison with *I*–*V* curves collected in the field. The results show that the proposed model can accurately simulate the entire *I*–*V* characteristic curves and maximum power points. Array power outputs were then predicted for three different sets of weather conditions. The effect of cell temperature on power output was clearly evident around noon on sunny days. The accuracy of the simulation model was evaluated using three statistical indicators, which showed that the model is in good agreement with field collected data. No significant difference existed indicating that this model is not only suitable for modeling the *I*–*V* characteristics but also for any general purpose power prediction. The model was further applied to comparisons between predicted and measured power to examine the reasons for the power loss which occurred in practice. It was found that PV power output from a standalone PV system can be limited by the status of the battery bank. The installation of a sufficient storage capacity or the training of local residents to better utilize the energy system, can help to reduce the potential power wasted in this way..

This research demonstrates that the PV simulation model developed is not only simple but useful for enabling system designers/engineers to understand the actual *I*–*V* curves and predict actual power production of the PV array, under real operating conditions, using only the specifications provided by the manufacturer of the PV modules.

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